Efficient Signal Processing and Anomaly Detection in Wireless Sensor Networks*

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Abstract. In this paper the node-level decision unit of a self-learning anomaly detection mechanism for office monitoring with wireless sensor nodes is presented. The node-level decision unit is based on Adaptive Resonance Theory (ART), which is a simple kind of neural networks. The Fuzzy ART neural network used in this work is an ART neural network that accepts analog inputs. A Fuzzy ART neural network represents an adaptive memory that can store a predefined number of prototypes. Any observed input is compared and classified in respect to a maximum number of M online learned prototypes. Considering M prototypes and an input vector size of N, the algorithmic complexity, both in time and memory, is in the order of $O(MN)$. The presented Fuzzy ART neural network is used to process, classify and compress time series of event observations on sensor node level. The mechanism is lightweight and efficient. Based on simple computations, each node is able to report locally suspicious behavior. A system-wide decision is subsequently performed at a base station.

Keywords Sensor networks, anomaly detection, pattern recognition

1 Introduction

Wireless sensor networks have a number of strengths such as distributivity, parallelism, redundancy, and comparatively high cost-effectiveness due to lack of wires. On the other hand, their tininess, need for long-term operation, and dependency on batteries impose severe restrictions on the system. Hence, services provided in sensor networks need to be lightweight in terms of memory and processing power and should not require high communication costs.

The goal of this work is to provide an office monitoring system which is able to distinguish abnormal office access from normal access. Therefore, office access patterns need to be classified. The access patterns vary in their time of presence. They are composed of signals, i.e., collected time series of observations of some

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phenomena, which are monitored on the sensor nodes. This classification problem faces mainly two restrictions in sensor networks. First, processing power and memory are limited on sensor nodes. Accordingly, complex pattern classification methods such as presented in [1] are difficult to be implemented on node level. Second, communication costs are high. Therefore, it is not possible to transmit the observed signals without further processing to a fusion center. A possible solution to the problem could be based on querying systems [2]. However, those events that have to be monitored need to be defined and declared by a system expert. The approaches require a priori knowledge about the occurring events and thresholds to determine the event boundaries, which prevents any dynamic anomaly detection. Context-aware and Time Delayed Neural Networks [3] have been applied to classify events that evolve over time. However, they need periodic learning and specific neural networks for every kind of occurring event. Apart from classification, anomaly detection has been gained some attention too [4], [5]. The focus of these approaches is very specific and comparatively high communication and computation costs are accepted. Anomaly detection has furthermore been addressed by Artificial Immune Systems (AIS) [6], [7]. These systems work similar as ART neural networks, but are less compact and require more memory.

In our work, signals monitored over predefined intervals are classified on sensor nodes by an instance-based learning algorithm, where prototypic event patterns are dynamically learned, and infrequently matched patterns can be replaced. This algorithm is comparatively lightweight and accounts for the constraints in wireless sensor networks. Both learning and classification are performed by a Fuzzy ART neural network. Such kinds of networks have been implemented for sensor networks [8], [5]. However, the current focus has been on merging multiple sensor readings at discrete time points, rather than processing time series of measurements in an efficient and accurate manner.

To solve the classification problem we propose a two-layered approach. The observed signals are periodically collected and classified on the sensor nodes. The classifications assign the signals to learned prototypes. These assignments (classification numbers) are then periodically sent to a fusion center where the classification of the system-wide access pattern is performed. Accordingly, on each sensor node a high compression level is achieved. The Fuzzy ART neural network is tailored to the specific requirements of wireless sensor networks.

2 Classification and Anomaly Detection

Adaptive Resonance Theory (ART) [9] is a special kind of neural network with sequential learning ability. By feeding new samples, an ART neural network is able to refresh an already known prototype if the sample is similar to it. Else, a new category is created unless the total memory capacity has been utilized. Initially, ART networks were developed for binary input patterns. However, in subsequent work (Fuzzy ART) the network architecture had been enhanced to accept analog input samples too. The principle architecture is shown in Fig. 1.

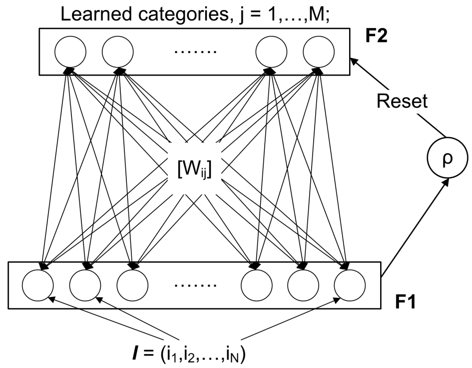

Fig. 1. Fuzzy ART neural network architecture.

A Fuzzy ART system operates unsupervised. It consists of two layers, a comparison layer F1 with N neurons and a recognition layer F2 composed of M neurons. Neurons in F1 represent the attributes of the input, while neurons in F2 represent categories (prototypes). Furthermore, there is a sensitivity threshold ρ, also called vigilance factor, which evaluates the similarity between a given input $\boldsymbol{I}$ and any of the learned categories in F2. Similarity is always determined according to the Euclidean distance between $\boldsymbol{I}$ and the current category. The vigilance factor has impact on the system behavior: the higher the vigilance factor is chosen, the more fine-grained is the memory. This requires many categories, though. A last parameter that has impact on the system behavior is the learning rate. The higher the learning rate, the higher is the impact of the current input.

Fuzzy ART-based Learning

input: Input vector $\boldsymbol{I}$;
ouput: Number representing category j to which $\boldsymbol{I}$ belongs;
begin
    Compute the activation α_j of each neuron in F2;
    Sort the α_j in descending order;
    for each α_j **do**
        Compute similarity s_j between $\boldsymbol{I}$ and category j;
        if $s_j > \rho$
            Update the weights in $W_{i,j}$;
            return Category number j;
    end
    if maximum number of categoris is not reached
        Commit uncommitted neuron n in F2;
        return n;
    else return -1;
end

The operation of a Fuzzy ART neural network is described in the pseudo-code above. Similarity is computed according to the weights stored in the matrix $W_{i,j}$. These weights represent the long-term memory of the system. The input vector $\boldsymbol{I}$ is compared to all categories. If $\boldsymbol{I}$ is similar to one of the stored categories (prototypes) the category number is returned as classification output and the weight matrix is updated. Else, either a new category is learned, i.e., if some memory in F2 is available, or the system returns -1.

Sensor networks have to face two main restrictions: Communication costs and memory constraints. On the other hand, anomaly detection requires the analysis of time series of signals. Fuzzy ART systems are ideally suited to meet these requirements: The input is sequentially processed, no buffering is required and time and storage complexity of a Fuzzy ART neural network are only in the order of $O(MN)$ [10], where M is the number of categories in F2 and N is the input vector size. The output of a Fuzzy ART neural network is the classification number of the input vector $\boldsymbol{I}$. Thus, a data compression of N to 1 is possible.

The sampling frequency is chosen depending on the observed signal. In the current implementation light is sampled 40 times in two seconds. The non-preprocessed input vector $\boldsymbol{I}$ has a size of 40 elements. To decrease this complexity, two discrete Haar Wavelet transforms [11] are applied on the raw times series. Thus, the size of $\boldsymbol{I}$ is reduced to 10. In addition to the needed reduction in sample size, the Wavelet transform also smooths the original input signal, which can either be interpreted as a smoothing of the original signal or as a generalization of the same. The discrete Haar Wavelet transform is applied as a simple digital Low Pass Filter (LPF), which can easily be performed on a sensor node. A data reduction factor of two for each application of the LPF is achieved.

With an unmodified Fuzzy ART network, non-classifiable signals evolve as soon as the memory is full. Any new pattern, even if it occurs frequently, could not be classified afterwards. This might make any evaluation difficult. Therefore, we support expiration. Based on an aging mechanism, always the oldest prototype is replaced with the latest one, else not classifiable, input sample. This approach is reasonable as frequently matched categories (normal behavior) will hardly be affected by the aging mechanism. Thus, anomalous behavior can be detected, even though infrequently used knowledge is forgotten by the system.

3 Signal Processing and Classification Performance

The performance of the Fuzzy ART neural network for anomaly detection and compression on node-level has been evaluated. TmoteSky [12] sensor nodes have been used. They consist of a microprocessor, 10 kB RAM, an IEEE 802.15.4 compliant radio, and a some sensors, whereof the light sensor has been used. Light is measured 40 times in an interval of 2 s. Two discrete Haar Wavelet transforms are applied. The resulting input vector $\boldsymbol{I}$ of size 10 is fed into the Fuzzy ART neural network. The comparison layer F2 allocates memory for 10 categories, leading to storage requirements in the order of 200 bytes for the Fuzzy ART network. The vigilance factor ρ is 0.75 and the learning rate is 0.1.

The goal of the evaluation is to detect and report flashlight periods, which impose frequent switches from dark to bright and vice versa, in a dark room. Two different patterns of light activation have been performed. Both started during daytime, lasted for 10 minutes (see Fig. 2). Each pattern has been repeated three times. The sensor node was placed in the middle of the room.

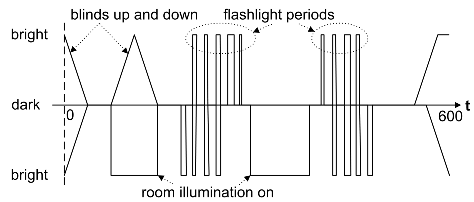

Fig. 2. Light pattern I (upper part) and light pattern II (lower part).

Two representative runs are shown in Fig. 3. The other runs are similar. Instead of the classification numbers, only state changes, i.e., category switches in the output stream of the Fuzzy ART network, are shown. Monitoring state changes is sufficient to distinguish exceptions from normal behavior. Thus the detection problem can be reduced to an analysis of sequences of binary decisions.

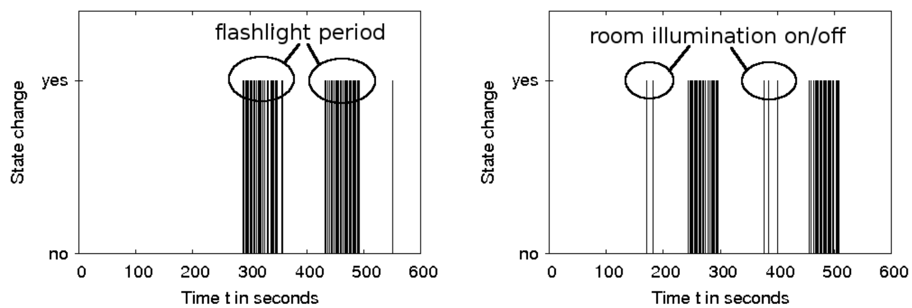

Fig. 3. Temporal state changes of the Fuzzy ART network.

In all experiments the lowering and raising of the sun-blinds did not lead to any state changes. Accordingly, the Fuzzy ART anomaly detector is able to adapt to slowly changing environmental conditions. Both flashlight periods introduced many different input signals $\boldsymbol{I}$, which resulted in many different classifications and accordingly in many state changes. The experiments with light pattern II contain two periods where the room illumination has turned on and off. This invokes abrupt illumination changes which are well observable by the few state changes before, respectively after the first flashlight period (on the left in Fig. 3). The average number of state changes in all twelve flashlight periods is 24.5 with a standard deviation of 2. Thus, a person moving with a flashlight could be easily detected by observing a certain number of state changes in a given interval.

4 Conclusions and Future Work

In this paper the compression and classification of anomalous behavior with a Fuzzy ART neural network on sensor node level has been addressed. Any observed time series (access pattern) fed to the system is mapped to a single classification value, which is sent to a fusion center. The Fuzzy ART neural network is self-learning, processes any input sequentially, needs no buffering of samples, and adapts to both, changing environmental conditions and new evolving signals. Finally, the high compression rate lowers communications costs. In future work the fusion of local anomaly reports on a dedicated node will be considered. The goal is a working anomaly detection system for office monitoring.

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